Threats to Adversarial Training for IDSs and Mitigation

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Abstract: Intrusion Detection Systems (IDS) are essential tools to protect network security from malicious traffic. IDS have recently made significant advancements in their detection capabilities through deep learning algorithms compared to conventional approaches. However, these algorithms are susceptible to new types of adversarial evasion attacks. Deep learning-based IDS, in particular, are vulnerable to adversarial attacks based on Generative Adversarial Networks (GAN). First, this paper identifies the main threats to the robustness of IDS against adversarial sample attacks that aim at evading IDS detection by focusing on potential weaknesses in the structure and content of the dataset rather than on its representativeness. In addition, we propose an approach to improve the performance of adversarial training by driving it to focus on the best evasion candidates samples in the dataset. We find that GAN adversarial attack evasion capabilities are significantly reduced when our method is used to strengthen the IDS.

1 INTRODUCTION

Currently, networks are open to many types of attacks, including denial of service (DoS), probing, and SQL injection. Intrusion detection systems (IDSs) are components that monitor either host machines or network activity to detect attacks and intercept them. Machine learning (ML)-based IDS has been identified as a solution to the common problems of expertly configured signature-based IDS, including the large number of rules to manage, limited detection capabilities, and high maintenance costs. However, this work concentrates on ML classifier-based IDS that use supervised learning. Classifiers are parametric functions with a large number of configurable parameters. This is accomplished during the training process, which optimizes their detection rates and avoids false alarms. The classifier takes as inputs collected data that has been divided into units describing the system's activity (packets, events, connections...). The predicted class is the classifier's output; it is either attack or normal traffic in the simplest case. Such a setting can be described as a two-side architecture, with the attacker responsible for performing attacks and attempting to evade detection and the defender responsible for training and deploying an IDS that offers the best trade-off between detection rate and false alarms. Many works discuss the quality of datasets that may not be sufficiently representative (Khraisat et al., 2019). This question is also raised in more generic works on training process quality and potential threats to classifier performances. (Gong et al., 2019). In this paper, we study the potential weaknesses in the construction and content of the dataset rather than its representativeness. To our knowledge, the two weaknesses we focus on have received less attention in the security domain. They impact the resistance to adversarial samples attacks, a well known approach to evade detection for IDSs based on machine learning, (Szegedy et al., 2014). Adversarial sample attacks involve using adversarial sample generation to learn how to turn IDS-ignorant attacks into attacks that can evade them while still having a malicious impact. Such transformations are possible using Generative Adversarial Networks (Goodfellow et al., 2014) among other generative approaches. Nonetheless, evading IDS detection and ensuring the malicious impact is not a trivial task as pointed out in (Backes et al., 2016) for malware detection.

In this work, we review previous work on well-understood models (Goodfellow et al., 2015) and datasets. In our contributions, we identify major threats to IDS robustness against adversarial sample attacks designed to evade IDS detection. Next, we propose and evaluate three approaches to mitigate these issues.

Section 2 formalizes the main concept about IDSs based on classifier besides identifying the known threats that affect an IDS's performance. Section 3 formally defines the main consequence of being able

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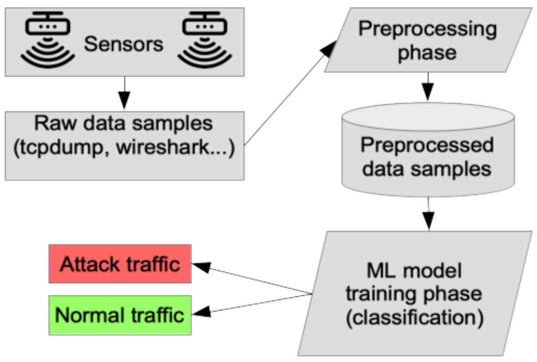
Sensors
Raw data samples (tcpdump, wireshark...)
Preprocessing phase
Preprocessed data samples
ML model training phase (classification)
Attack traffic
Normal traffic
Figure 1: Deployed architecture of classifier based IDS.

to generate adversarial samples that remain attacks without testing. Furthermore, it introduces the threats this situation entails and presents mitigation strategies. Sections 4 and 5 present the experimental assessment of the risks represented by the threat we identified and the performance of the mitigation strategies.

2 DATASET QUALITY AND ADVERSARIAL TRAINING

This section recalls the main concepts of adversarial training and ML-based IDS. We study why the training set used to set up IDSs needs to be cleansed or extended to improve IDS detection capabilities and robustness. We highlight that one of the quality criteria used to remove problematic data needs to be revisited when creating adversarial datasets.

2.1 Classifiers with IDS

Network raw data refer to data provided by network sensors, as depicted in Figure 1. Sensors represent observation capabilities of network activity from routers, firewalls or host machines. This data is organized and merged into observation units corresponding to an element of network activity, called a sample. An IDS incorporating a classifier for attack detection is fed with samples of data collected by sensors. As depicted in figure 1, the sample goes through various processes before being processed by a classifier that determines for each sample whether it belongs to an attack or not.

Definition 1 (Raw Sample)**.** A *raw sample* is a tuple of n values respectively of types T_1, ..., T_n. The raw sample type T_R is $T_R = T_1 \times ... \times T_n$.

The PCAP format is the type of raw sample usually used: it is sufficiently detailed that the activity can even be replayed from the raw sample. Basically, raw samples are expected to be detailed enough to be able to decide whether a sample corresponds to normal activity or attack. Let L be the set of possible labels: $L = \{normal, attack\}$.

Definition 2 (Raw Labeled Sample and Dataset)**.** A *raw labeled sample* is a couple (x, y) where $x \in T_r$ and $y \in L$. A *raw labeled dataset* is a set of raw labeled samples.

The raw sample type often relies on non-numeric types to capture metadata about packets or application behaviors. Therefore, the values of raw samples can be of very diverse types (e.g., binary, categorical, numeric, strings). It is extremely difficult to feed a classifier with such data without first transforming all these types into scalar normalized values. This step is called pre-processing. Let call *prep* the function that produces IDS scalar inputs from raw samples R. Therefore, *prep* function takes elements of T_R and produces a vector of values q in $[0,1]$, we now use T_P such that $T_P = [0,1]^q$.

Definition 3 (Preprocessed Samples and Labeled Dataset)**.** For any raw sample x, $prep(x)$ is a *preprocessed sample*, and for any raw labeled dataset D, $prep(D) = \{\{(prep(x_i), y_i) | (x_i, y_i) \in D\}\}$, is the corresponding *preprocessed labeled dataset*.

To apply *prep* to a labeled dataset, one has to apply it to the raw sample portion of each labeled sample. In the machine learning community, a dimension of a sample is called a feature. A labeled sample is said to be an *attack sample* if its label is *attack*, and a *normal sample* if it is *normal*. Each labeled dataset can be split in two subsets respectively called *normal traffic* and *attack traffic*.

Definition 4 (Normal and Attack Traffic of D)**.** Given a labeled dataset D (raw or preprocessed), the *normal traffic* of D denoted $N(D)$, and the *attack traffic* of D denoted $A(D)$ are defined as follow:

$$\begin{aligned} N(D) &= \{(x_i, y_i) | (x_i, y_i) \in D, y_i = normal\} \\ A(D) &= \{(x_i, y_i) | (x_i, y_i) \in D, y_i = attack\} \end{aligned}$$

A labeled dataset is necessary when training a classifier, or defining its parameters; such a dataset is called a training dataset. Datasets may contain problematic samples, either due to errors in sample collection or due to poor observational or pre-processing capabilities.

Definition 5 (Contradictory Samples and Dataset)**.** Two labelled samples (x_1, y_1) and (x_2, y_2) are *contradictory samples* if and only if (iff) $x_1 = x_2$ and $y_1 \neq y_2$. A dataset D is a *contradictory dataset* iff it contains contradictory samples.

A classifier is a parametric model that must be configured, and the training process is responsible for determining the appropriate parameters. The training of a deep or standard machine learning model consists of feeding samples to it and tuning its parameters to minimize a loss function (defined to penalize predicted labels from those of the training set). Hence, a contradictory dataset impairs this process as it prevents minimizing this loss function properly.

The following subsection shows how a malicious adversarial sample can evade detection and how it can be mitigated and improve the dataset used for training.

2.2 Adversarial Samples and Training

In (Papernot et al., 2017), the authors identify a meta-attack procedure that can abuse the classifier's decision by mutating a pre-processed sample. This mutation aims to slightly modify the activity to change its result while providing a different classifier label. This type of meta-attack can be used to perform an evasion attack: an attack to hide malicious activity.

An *adversarial sample* or *malicious adversarial sample* (*MAdv*) is obtained by adding a disturbance on each dimension (which we call a mutation) of an existing sample so that the predicted label of the sample before and after the disturbance is added differently. In the case of evasion attacks, the attacker focuses on crafting adversarial examples for attack samples. As stated above, the purpose here is not to generate legal traffic from the attack traffic but to change the output of the classifier and retain the malicious impact.

Definition 6 (Adversarial sample generator)**.** An *adversarial sample generator AG* is a function that produces a *MAdv* from an input attack sample and a value assumed to be chosen at random.

The second parameter is intended to ensure that the attack generator is a deterministic function that can be used to produce many different *MAdv* depending on the random value provided as input.

An *AG* is said to be correct if from an originate attack sample *x* it only generates samples that are actually attacks (and in practice this gives the same kind of consequences as *x*). The efficiency of an *AG* against an IDS is measured as its likelihood of producing an attack sample that is classified as a normal sample by the IDS.

Note that an efficient but incorrect *AG* is as useless as a correct but inefficient generator from the point of view of the evasion attack.

Deep neural network models are known to be vulnerable to *MAdv*s (Goodfellow et al., 2015). Hopefully, efficient adversarial defense approaches have been proposed to prevent these attacks (Qiu et al., 2019). According to the literature, adversarial training or its extensions remain the most effective approaches to improve the robustness of classifiers against *MAdv*s (Ren et al., 2020).

Adversarial training involves extending a training dataset *D* with *MAdv*s before training an IDS. It relies on an *AG* that is used by the defender to generate *MAdv*s intended to evade detection of IDS trained on *D*. The *MAdv*s generated by *AG* are then added to *D* and the *IDS* is retrained on the new dataset.

The purpose of using *AG* is to add samples to the training without the need to actually execute them. Their label would be inferred. Otherwise, the cost of significantly expanding the dataset would be prohibitive.

Three aspects affect the quality of the adversarial training, the number of samples added (because it changes the distribution of *D*), the choice of attack samples that are modified and the quality of the alteration. Surprisingly, the choice of attack generator inputs and how adversarial training is actually implemented remains poorly studied in the security community.

2.3 Problem Statement

Without dedicated guidelines, an attack generator would alter all the features of an attack sample. A purely random alteration of a sample may not preserve the malicious impact of a sample. Yet, suppose first that we know how to generate only *MAdv*s. The problem is that, in some cases, it would be possible to create a sample through adversarial training identical to a sample labeled as normal in the dataset used to train an IDS. While this is possible, although it is not directly a contradictory data set, it still raises problems and poses threats to the approach or even to the IDS itself.

Therefore, the issues raised by these observations are as follows:

- Is there a concept similar to a contradictory training data set that needs to be taken into account when applying adversarial training?
- Can the criterion used to define effective *MAdv*s be exploited to boost adversarial training, either by helping to select better *MAdv*s or by reducing the cost of the approach.

In the next section, we identify the notion of the impactful neighborhood and explain how this can be a threat to adversarial training in the first place, but also how understanding this concept helps to design better sampling approaches of the *MAdv*s.

3 THREAT TO ROBUSTNESS OF IDS AND MITIGATION

This section presents the core concepts of our approach and contribution to better handle and understands adversarial training.

3.1 Extending the Contradictory Set

Our work is motivated by the following observation: the label of an adversarial sample is set to the label of the sample that has been modified and can then be added to a training dataset. Those actions are carried out without quality checks and raise issues. Usually, samples are obtained through observations, and thus the label is the observed impact. Yet, in the case of *MAdv*s no real activity is necessary to "obtain" a sample. From a defender, it helps to extend training sets at almost no cost, because no real observation is necessary to obtain new samples. Yet, it relies on the assumption one can ensure an *AG* can only generates attack samples. It implies that we know how to apply perturbations in a neighborhood of each sample that does not actually change its impact.

Definition 7 (Impactful neighborhood of an attack sample)**.** The *impact neighborhood of an attack sample x*, denoted $INA(x)$, is the set of all possible mutations applied to x that does not change its actual impact.

By extension $INA(A(D))$ is the union of the impactful neighborhood of all attack samples of D. By definition, a correct *AG* only produces elements of $INA(A(D))$. Because adversarial training essentially builds training sets from subsets of D and $INA(A(D))$ The notion of contradictory data set should be explored for $D \cup INA(A(D))$.

Definition 8 (Extended contradictory dataset)**.** The extended contradicting set of a dataset D, given *INA* is the set of all contradictory samples contained in $D \cup INA(A(D))$ and is noted $EC_{INA}(D)$ (more formally $EC_{INA}(D) = \bigcup_{x}\{(x, normal), (x, attack)\}$ with x such that $(x, normal) \in D$ and $(x, attack) \subseteq EC_{INA}(D)$).

The INA index in EC_{INA} will be omitted as we only consider one version of it. $EC(D)$ contains all contradicting samples originally in D but also all the contradicting samples that could be obtained through adversarial training. Figure 2 depicts a simplified dataset D with four elements including two attacks, x_1 and x_2. Let assume their *INA* contains only four elements : themselves plus the results of two perturbations, p_1, and p_2. In this case, we assume $x'_1 = x_1 + p_1, x'_2 = x_2 + p_1, x''_2 = x_2 + p_2$ are all samples not

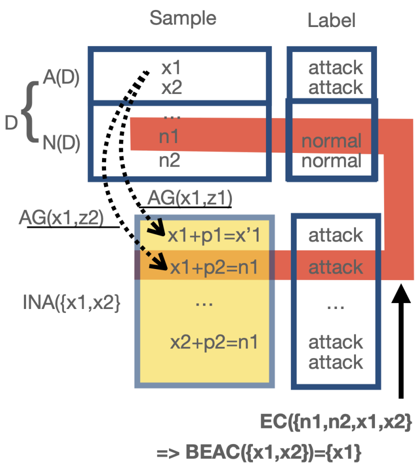

Figure 2: *MAdv*s, *BEAC* and EC.

included in D, yet $x_1 + p_2$ is in fact equal to n_1. In this context, $EC(D) = \{(n1, normal), (n1, attack)\}$ as $(n_1, attack)$ is an adversarial attack sample that could be generated. Recall that a classifier trained on D, is very likely to predict label y for sample x if $(x, y) \in D$. Therefore, an IDS trained on a dataset containing D has a high likelihood to predict *normal* as a label for n_1. From the attacker's point of view, applying the attack generator on samples that are transformed into elements of $EC(D)$ could represent its best chance of success. These samples will be called Best Evasion Attack Candidates (BEAC) and are part of D as shown in Figure 2.

Definition 9 (Best evasion candidates of a dataset)**.** The set of *Best Evasion Attack Candidates of a dataset D* is defined as $BEAC(D) = \{w \mid INA(w) \cap EC(D) \neq \emptyset\}$

Figure 2 depicts this situation in which two contradicting samples can be obtained due to adversarial training, and details the role of D, $INA(D)$, $EC(D)$, and $BEAC(D)$

An attack generator can be created by generative approaches (GANs, autoencoders ...). In this case, the attack samples of $EC(D)$ thus contain the right samples for training an attack generator to attack an IDS trained with D as is. Thus, the knowledge of $EC(D)$ and $BEAC(D)$ can be the source of various threats to IDSs performances.

3.2 Adversarial Training Threats

The concept of the extended contradictory dataset raises several questions on the way *MAdv*s for IDSs are generated and handled.

Assume the attacker knows the INA of its attack samples. An attack generator is either in a white box or black box setting. Black box assumption is considered equivalent to assuming that the attacker knows a dataset equivalent (same distribution) to the one used to train the IDS (before any adversarial training). Thus, both have similar $EC(D)$. We study the case where the attacker knows $BEAC(D)$, but the defender applies adversarial training without particular care.

The first threats to IDS performances are due to a defender that does not know how to explore $INA(x)$ of an attack sample x. This situation must be taken into account as we have noticed that to our knowledge only NSL-KDD explicitly provided insights to define the notion of impactful neighborhood.

The consequence of this situation is that the attack generator used by the defender does not guarantee that generated samples are actual attacks. We assumed previously to use only correct attack generators for simplicity. However, in practice, this situation is not guaranteed for the defender. Recall that adversarial training extends a dataset D with samples for which the label is set to attack without actually observing the activity. Therefore, we have two cases, either the defender sets blindly labels to *attack*, or it checks whether *MAdv*s are actual attacks. The former case is called the poisoning threat, and the latter is called the testing cost threat.

Definition 10 (Poisoning Threat)**.** If adversarial training is performed for an IDS using an *AG* for which it cannot prove that $AG(w,z) \in INA(w)$, then this training procedure is said to poison the IDS training dataset.

Indeed, there is a chance that the generated samples correspond to actual normal activities instead of attacks. If such a normal activity is labeled as an attack, then it is a dataset poisoning situation that threatens the availability of normal activities.

The alternative approach is to test each adversarial attack sample that would be added for training (second case). The activity has to be carried out and observed. This is no longer adversarial training as it requires real observation. It is a regular dataset extension for which the defender must pay the cost of executing each sample and observing it.

Definition 11 (Testing Cost Threat)**.** Consider that adversarial training is performed for an IDS using an attack generator *AG* for which it cannot be proven that $\forall z,\ AG(w,z) \in INA(w)$, and that the defender tests the impact of each generated *MAdv*, then this training procedure is said to suffer from a testing cost threat.

If someone applies this approach given the usual size of adversarial training dataset, it can be intractable or too costly. Now suppose the impactful neighborhood of an attack sample is defined and used by the defender to avoid previous threats. In this context, if we do not remove normal samples of D that do belong to $EC(D)$, then we risk adding to D, through adversarial training, attack samples that are very similar or equal in value but with different labels. Even if samples are not contradictory, adding samples very similar with distinct labels might significantly disrupt the training process (having a large gradient even with small changes on input makes training difficult). This increases the risk of false prediction.

Definition 12 (Confusing Normal Sample Threat)**.** If D' is a training dataset that extends D with adversarial samples, then D' is said to be subject to confusing normal sample threat if it contains normal samples that belong to $EC(D)$.

Indeed, if a dataset with *MAdv* does contain confusing normal samples, this can increase the likelihood of evasion attack success for attack samples in $BEAC(D)$ (attack samples that once modified may belong to $EC(D)$). The last case is related to the sampling strategy of the different attack samples. Indeed, if a category of attack is more likely to happen, it is relevant to acquire more samples of it to improve detection capability. Conversely, if an attacker knows that an evasion attack is more likely to succeed for an element of $BEAC(D)$, then it is more likely that this attack will be carried out because of a higher evasion rate *a priori*.

Definition 13 (Best Evasion Attack Threat)**.** The *best evasion attack threat* corresponds to the situation where an attacker focuses on applying evasion attacks only for elements of $BEAC(D)$ for an IDS trained on D.

This threat account for attackers that focus on applying evasion attacks only on attack samples with the highest likelihood to evade detection. We now provide the mitigation strategies for these threats.

3.3 Mitigation Strategy

We identified four threats to an efficient usage of adversarial training related to INA. Note that the first two threats cannot be mitigated; they represent situations in which adversarial training is either too costly or risky as it may significantly reduce the system's availability. In practice, even if there is no formal definition of the impactful neighborhood, the concept is implicitly defined. So now, let us consider the two last threats: the confusing sample threat and the best evasion attack focus threat.

Definition 14 (Sample Removal)**.** This mitigation strategy consists in removing normal samples from D

that belong to $EC(D)$.

This approach avoids normal samples for members of $EC(D)$. Yet, these samples can still be obtained through adversarial training. In order to reduce the likelihood of detection miss, we can change their label in D instead of removing them.

Definition 15 (Pessimistic Relabelling)**.** Relabel any normal sample from $D \cap EC(D)$ as attacks.

We now introduce mitigation for the last threat. *MAdv* generation is based on the selection of attack samples on which an evasion attack generator is applied. The selection of attack samples on which the attack generator is applied is called *attack sampling*. Attack sampling is almost never discussed on the attack side and is assumed to be uniform. Yet, attackers that restrict themselves to $BEAC(D)$ elements would be less likely to do so either because they do not have enough samples in this area or because the attack generator creates an element of $EC(D)$. Our mitigation strategy would be to change the proportion of $BEAC(D)$ elements when sampling $A(D)$ during adversarial training.

Definition 16 (Oversampling of *BEAC*)**.** This strategy consists in increasing the likelihood of generating *MAdv*s from elements of *BEAC*.

It allows training the IDS to be more efficient in detecting them. A first expected effect is to obtain samples in $EC(D)$ to force predicting the attack for this set. A second expected effect is that a good detection on $BEAC(D)$ could be generalized to other samples. First, the impact of confusing sample and best evasion attack focus threats need to be assessed on IDS without mitigation. Secondly, it is also necessary to check that the proposed mitigation approach actually mitigates them. Next section details the experimentation campaign conducted to assess all these aspects on a dataset for which the INA concept is defined.

4 ASSESSMENT METHOD AND ARCHITECTURE

This section discusses the different assessment objectives and metrics used. The experimental framework and dataset are then described.

4.1 Metrics and Objectives

First, we need to determine the performance metrics for evasion attacks and adversarial training. The objective is to identify the extent to which the performance of the attack generator correlates with the content of the Extended Contradictory set and how the proposed mitigation strategies perform to address the identified threats. We use the usual IDSs performance metrics derived from confusion matrices (Wang, 2018). Testing an IDS requires a labeled test dataset without evasion attack, e.g. an Original Test Dataset OTD. To test the IDS without evasion attack, we simply submit OTD samples to the IDS. To test the IDS against evasion attack, an attack generator is applied to the members of OTD before submitting them to the IDS. We check IDS predicted labels for the submitted samples to compute the number of true positives TP, false negatives FN, false positives FP, and true negatives TN.

The Recall is one of the most used metrics to determine if an attack would be detected. Let suppose TP and FN are computed for an IDS tested with OTD, on which F is first applied. F is either the identity function, noted *id*, or an attack generator. The recall of this experiment is noted and defined as:

$$Recall_F^{IDS}(OTD) = \frac{TP}{TP+FN}$$

Then, $Recall_{id}^{IDS}$ is the recall of IDS tested without evasion attack applied, and $Recall_G^{IDS}$ is the recall of IDS tested against the attack generator G. We are interested in the extent to which the Recall is affected by evasion attacks and measure it through the *evasion increase rate (EIR)* of a generator G defined as follows:

$$EIR_G^{IDS}(OTD) = 1 - \frac{Recall_G^{IDS}(OTD)}{Recall_{id}^{IDS}(OTD)}$$

The last metric used is the *evasion reduction rate (ERR)* which compares EIR for the same attack generator but against different IDSs.

$$ERR_G^{IDS_1,IDS_2}(OTD) = 1 - \frac{EIR_G^{IDS_2}(OTD)}{EIR_G^{IDS_1}(OTD)}$$

ERR compares how well IDS_2 resists to G compared to IDS_1. We use ERR only to compare an IDS trained without adversarial training to the various IDSs that take advantage of the mitigation strategies.

4.2 Dataset, Dataset Extension

This subsection describes the dataset and how we use the GAN-based generator.

4.2.1 Dataset

The choice of the dataset was difficult. To our knowledge, the only one to provide a clear definition of *INA* is NSL-KDD. Still, this dataset is considered outdated as it does not cover recent attacks. However, many papers used it and overlooked the threats we identified. Therefore, we decided to conduct the assessment on NSL-KDD because it provides a clear definition of the *INA*, and this dataset is well understood. This dataset categorizes attacks as Denial of Service (DoS), User to Root (U2R), Root to Local (R2L), and Probe. The NSL-KDD training dataset includes 41 features and class identifiers for each record. The concept of *INA* is defined through the notion of function features: the dimension that should not change (Lee and Stolfo, 2000). Hence, the *INA* is obtained by changing all non-function features of a sample. NSL-KDD samples' features are split into four groups: Intrinsic, Time-based, Content, and Host-based. Not surprisingly, the functional features are different for each attack category:

- DoS attacks: Intrinsic and Time-based
- U2R attacks: Intrinsic and Content
- R2L attacks: Intrinsic and Content
- Probe attacks: Intrinsic, Time-based and Host-based

In order to stick to our models, binary classifiers, the dataset is split in 4 datasets, one per attack type, which only retain the targeted attack type. We will focus on normal, DoS, and probe samples as the others are too few. It should be noted that after searching for the *BEAC* set on the training dataset of NSL-KDD restricted to DoS and Probe attacks, we found that $BEAC(D)$ contained only DoS samples that represent 3.74% of DoS samples. In this dataset, the samples contain categorical attributes, such as protocol type or flags. We applied the usual pre-processing approaches on these samples to obtain fully scalar attributes.

4.2.2 Generative Adversarial Network (GAN)

We assume that GAN-based generators are black-box evasion attack generators. GAN-based attacks target pre-trained IDS models and repeatedly update the parameters of two components, the Generator and the Discriminator. The Generator is trained to mutate the non-functional features of the attack samples to generate *MAdv*s. The generator input is made of an attack sample concatenated with a random vector (it is compliant with the attack generator definition). The Generator is trained to evade discriminator detection, but the discriminator is trained to mimic the IDS. Each component has its own loss function: Discriminator is penalized when a sample is classified differently by the IDS, and the generator is penalized when generating samples that do not evade the IDS. Thus, among the key parameters of the Generator and Discriminator, there is the number of update iterations called epochs. We consider GAN trained here either on 100 or 1000 epochs as both are well-spread constants in security. A Generator of type $GAN-N$ would denote a Generator trained in N epochs. We also consider the best Generator ever observed against the IDS as the optimization process is not guaranteed to be monotonous. We implement training set extension and adversarial training as explained in algorithm 1 to produce *MAdv*s using $GAN-100$ type of generators. Generators are used on both sides: to extend the IDS training set but also on the attack side to apply evasion attacks and thus test our approaches. They all suffer from variability issues. On the attack side, we handle it by independently repeating the training of 50 generators to assess a generator type performance against an IDS. On the defense side, we ensure that the training continues or is restarted as long as the generator does obtain an EIR threshold (here 0.99 for DoS attacks). This ensures that the defense, to its knowledge, is using a decent generator.

Algorithm 1: Adversarial training of an *IDS*.

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Input: OD (an original dataset), IDS (an IDS trained on OD), S (an extension size factor), r (a rate of sampling of $BEAC(OD)$;
Output: Best Generator $best\_G$, re-trained $IDS$ on extended dataset $D_{ext}$;
1: procedure ADV-TRAIN $IDS(OD, IDS, S, r)$
2:     initialize $Gen$ and $Disc$, initial generator and discriminator of a GAN of type $GAN-100$
3:     Train $Gen$, $Disc$, using $Gen(OD)$ labeled by $IDS$, store each Generator with its evasion score.
4:     Choose the best attack generator $Gen$, noted $best\_G$;
5:     Use $best\_G$ to generate $MAdv$s from elements of $A(OD)$ to create $D_{ext}$ so that the added elements represent S times the size of $OD$. Moreover, the proportion of added elements created from elements of $BEAC(OD)$ has to be $r$.
6:     Re-train $IDS$ on $D_{ext}$;
7: end procedure
```

5 EXPERIMENTS AND RESULTS

Our experimentation consists in testing IDS trained on different datasets with adversarial training and/or mitigation strategies. In order to identify those IDSs, we follow this notation: $IDS-X-sr-option$ where sr and $option$ are both optional. X represents the dataset considered for training (detailed later). The parameter *sr* denotes the sampling rate chosen for $BEAC(X)$ if applied (not provided if unchanged). The *option* parameter indicates whether removing confusing normal sample, noted *wn* for without normal, or relabelling them as attacks, noted *na* for normal as attack, have been applied.

5.1 Threat Level Without Mitigation

We need to determine whether the existence of a non-empty *BEAC* set is problematic. As previously stated, probe and DoS attacks illustrate two distinct situations. If we compute the BEAC set of NSL-KDD, it contains no probe attack sample but DoS samples. Let thus train two IDSs, one for Probe and on for DoS attacks and see how they behave. We need a training dataset to detect DoS samples, it contains normal and DoS samples of NSL-KDD training dataset, noted OD_{DoS}. The second data set contains normal and Probe samples of NSL-KDD training dataset, noted OD_{Pr}.

We train two batches of 50 GANs, following the architecture of $GAN-100$, respectively against $IDS-OD_{Pr}$ and $IDS-OD_{DoS}$. We observe that evasion attacks reach an average *EIR* of above 0.99 for $IDS-OD_{DoS}$ and is 0 for $IDS-OD_{Pr}$. It shows two situations that are consistent with our claim of the role of *BEAC* in evasion attack success. Note that the IDS trained has shown usual performances, e.g., as in (Vinayakumar et al., 2019), of ML-based IDSs. Hence, we have a 0.85 recall (ability to detect attacks) for $IDS-OD_{dos}$ on non adversarial samples. The next step is to understand how efficient is the adversarial training for different size factor parameters. Here, we test an adversarial training for size factors of 1, 2, 5 and 10, leading to extended datasets for $AT1$, $AT2$, $AT3$, and $AT4$. Each dataset is used to train an IDS without any particular mitigation of identified threats. These IDS have been tested against strong

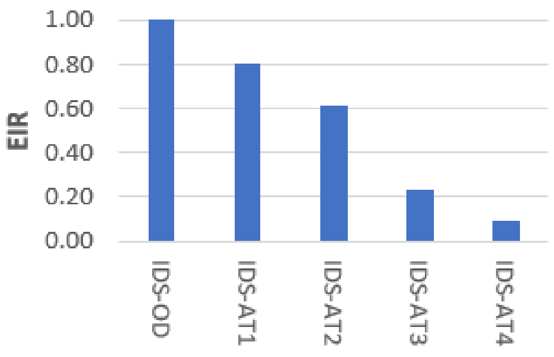

Figure 3: The average EIR for fifty $GAN-1000$ Generators vs $IDS-AT_1$, $IDS-AT_2$, $IDS-AT_3$ and $IDS-AT_4$.

attack generators of type $GAN-1000$ to better understand their performances, and results are presented in Figure 3. We notice that the risk of the adversarial evasion attacks drops significantly from 100% EIR on $IDS-OD$ to reach 9% EIR on a very costly IDS in terms of training, which is $IDS-AT_4$. Adversarial training works well but at the expense of scaling factors that are 5 or 10 times the size of the original dataset. Training an IDS on 10 times larger datasets has a linear effect on the training cost and may not be accepted. Note that this adversarial training has not impaired the performance of *IDSs* when no evasion attack is applied, as shown in the first three lines in Table 1.

In the following subsections, we perform experiments to evaluate our mitigation strategies described in 3.3.

5.2 Confusing Samples Mitigation

This subsection evaluates the impact on the performance of both regular and robust IDS when the two mitigation strategies, sample removal, and sample pessimistic relabeling (section 3.3) are applied.

5.2.1 Effect on Regular IDS Performance

As pointed out, confusing samples can make it harder for the IDS to resist attack generators. To assess the confusing sample threat on the regular IDS resilience, we train two IDSs. The first one is called ($IDS-OD-wn$) trained on OD without the normal samples applying the sample removal mitigation. The second one is $IDS-OD-na$ trained on OD in which we relabeled the confusing normal samples as attacks as proposed in the sample pessimistic relabelling mitigation. These IDS are not designed to be resilient

Table 1: Performance metrics of various IDS models.

IDSs	Precision	Accuracy	F1 score	Recall
$IDS-OD$	85.8	86.4	84.4	85.1
$IDS-AT_2$	82.4	86.2	84.6	86.9
$IDS-AT_4$	88.4	87.6	85.2	82.2
$IDS-OD-na$	88.1	87.9	85.7	83.4
$IDS-AT_2-25$	87.6	87.3	84.9	82.5

to evasion attacks. Thus, we use only Generator of type $GAN-100$ trained specifically against $IDS-OD$ and test them on $IDS-OD-wn$ and $IDS-OD-na$. We observe that the attacks still manage to evade $IDS-OD-wn$ completely.

However, the average *ERR* for $IDS-OD-na$ is 0.5 in this case. Note that we use weaker generators in this subsection compared to before. These results are encouraging as relabelling is a very cheap adversarial training. Indeed, the number of confusing samples is very limited compared to all normal samples (less than 1%). Yet, normal samples related to $EC(OD)$ seem very useful for adversarial training.

Let now consider adversarial training with these mitigation strategies.

5.2.2 Effect on Robust IDS Performance

We investigate the mitigation approaches of confusing samples combined with IDS reinforced with regular adversarial training. We assess the performance using $IDS{-}AT_2$, $IDS{-}AT_2{-}wn$ e.g. with sample removal mitigation and $IDS{-}AT_2{-}na$ using the sample pessimistic relabeling mitigation. This time, we use 50 $GAN{-}1000$ generators against each of these IDSs. Table 2 summarizes the results.

Table 2: ERR mean over the fifty $GAN{-}A_1{-}1000$ attacks on $IDS{-}AT_2$, $IDS{-}AT_2{-}wn$ and $IDS{-}AT_2{-}na$.

	$IDS{-}AT_2$	$IDS{-}AT_2{-}wn$	$IDS{-}AT_2{-}na$
ERR mean over 50 experiments	0.39	0.57	0.43

The ERR of the IDS without mitigation but with adversarial training on AT_2 remains low at 0.39. However, the first mitigation strategy, sample removal, performs significantly better this time. It increase the ERR by almost 50% to 0.57. Surprisingly, the relabelling strategy did not perform as expected, with a very small increase in ERR. Without mitigation, there is a real gap on the ERR of adversarial training of scaling factor 2, i.e. 0.39, and scaling factor 5, i.e. 0.83. Hence, we observe that simply removing few normal samples from the training data set reduces this gap by 50%. It provides a mean to reach a given ERR level with a significantly lower scaling factor.

In the next subsections, we examine the effect of the oversampling strategies on the $BEAC$ set compared to regular adversarial training with uniform sampling.

5.3 Adversarial Training on *BEAC* Set

Here, we consider adversarial training datasets built by controlling the sampling rate of elements from $BEAC$.

This last set of experiments aims to compare the effect of the last proposed mitigation compared to the sample removal and sample relabeling ones. We consider sampling rates of $BEAC$ in $\{0.10, 0.20, 0.25, 0.35, 0.50, 0.75\}$. We define the sr parameter value to denote percentages. Hence, $IDS{-}AT_2 - 25$ represents an adversarial training on a dataset with a size factor of 2 and a sampling rate of 0.25. Again, we test $GAN{-}1000$ generators against IDSs trained with an adversarial training set of size factor of 2, e.g., $IDS{-}AT_2 - j$ family.

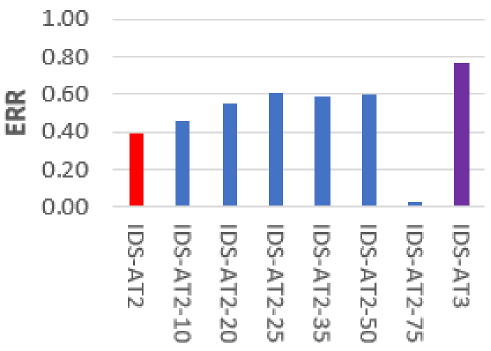

Figure 4: Average ERR on 50 $GAN{-}1000$ generators against $IDS{-}AT_2 - j$ for various j.

Figure 4 outlines the result of this experiment. The results reveal that the adversarial evasion attacks are significantly less effective in the majority of these IDSs when compared to $IDS{-}AT_2$ but for $IDS{-}AT_2 - 75$. However, this situation is expected as a too high sampling rate prevents the IDS from correctly detecting evasion attacks applied to attacks in $A(D) - BEAC(D)$. A sampling rate between 20% and 50% seems to be equivalent. This mitigation yields similar results to the sample removal approach with an ERR close to 0.6. Moreover, it seems not too difficult to take advantage of it, as the interval of sampling rates yielding similar ERR is large. Furthermore, using oversampling of $BEAC$ mitigation narrows the margin between the performance of $IDS{-}AT_2 - 25$ and $IDS{-}AT_3$ as the difference in ERR is almost divided by two, as one can see in Figure 4.

6 RELATED WORK

(Gong et al., 2019) provide criteria to define better sampling strategies for datasets and the use of diversification approaches to improve the training of generic classifiers. Yet, they do not consider the specificity of IDS as security classifiers or even the specificity of adversarial samples. With the recent advancements in machine learning research, adversarial attacks piqued the interest of researchers in a wide variety of domains. As a result, network security faces critical challenges from adversarial attacks as a sensitive and complex field. However, a few researches focus on the sampling strategy of $MAdvs$ in order to establish a fair balance between IDS training performance and detection capabilities against adversarial evasion attacks. In (Khamis et al., 2020), they generated *MAdv*s using two methods, either by mutating all the dimensions of attack samples or by mutating the 16 obtained principal components using Principal Component Analysis (PCA) as a dimensionality reduction technique. However, in either case, the *MAdv* generation was obtained without taking into account the impactful neighborhood of the attack samples. Therefore, the preservation of attack behaviors is not assured following the mutation process.

To our knowledge, all techniques that take INA into account define attributes that split attack samples as functional or non-functional. This separation of features is typically performed manually by a domain expert such as in NSL-KDD or through statistical or machine learning methodologies. (Lin et al., 2018), (Zhao et al., 2021) and (Usama et al., 2019) proposed to craft *MAdv*s using GANs. During the mutation process, they considered the impactful neighborhood of attack samples into account as they preserved the attack behavior by keeping the functional features of these samples unaltered, using the same criteria described for NSL-KDD. Whereas in (Alhajjar et al., 2021), (Chauhan and Shah Heydari, 2020), and (Msika et al., 2019), each of these works makes use of statistical tools or deep learning methods such as Shapley Additive Explanations (SHAP) (Lundberg and Lee, 2017) to define the impactful neighborhood of the attack samples. However, those tools define the attack's functionality solely based on the dataset's statistical properties, not on the attack samples' semantics. Although both categories perform very powerful adversarial evasion attacks, one shortcoming of these works lacks an examination of the effect of the confusion samples or *BEAC* set on the robustness of the IDSs when adversarial training is used.

To our knowledge, no work in the literature focuses on assessing the dataset after the mutation of *MAdv*s . This paper aims to examine the threats linked to the current generation process used in adversarial training. Furthermore, we propose a new method to improve the performance of the adversarial training for IDS by adjusting the sampling strategies of adversarial samples to account for confused samples and the *BEAC* set.

7 CONCLUSIONS

This paper examined the effect of a non-empty contradictory dataset on IDS robustness performance in the presence of adversarial samples. First, we identify the main threats that could lead to extending the contradictory set during adversarial training, including the poisoning threat, the threat of confusing normal samples, and the threat of the best evasion attack candidates (*BEAC*). In addition, we proposed three mitigation strategies to improve the performance of adversarial training by taking advantage of the impactful neighborhood of attack samples and focusing adversarial training on the *BEAC* set.

In future work, we will investigate the effect of the overall training approach on the IDS performance by specifying one IDS to detect regular attacks and another one to detect adversarial evasion attacks (in particular *BEAC* samples). In addition, we want to investigate the applicability of the proposed approach used with different sampling strategies such as those in (Picot et al., 2021).

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